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Multilayer Neural Network based on MIMO and Channel Estimation for Impulsive Noise Environment in Mobile Wireless Networks

Mohammed Amin Almaiah[1], Mohammed Al-Zahrani[2]
[1]Assistant Professor, Computer and Information Science, King Faisal University, Saudi Arabia
[2] Associate Professor, Computer Networking, King Faisal University, Saudi Arabia

ABSTRACT
Multiple Input Multiple Output (MIMO) system has several input and output antennas for executing the data transmission. Channel Estimation (CE) is required in MIMO, to achieve the effective signal transmission over the various amount of antennas in mobile networks. By using CE over the MIMO, the noiseless data transmission is performed. Hence in this paper, a Multi layer Neural Network (MNN) is used for identifying the CE and this system is named as Multi-layer Neural Network- MIMO-Digital Filter (MNN-MIMO-CE) is proposed for blind channel equalization. The MNN-MIMO-CE has Feed-forward Artificial Neural Network (FANN) with back propagation in Levenberg-Marquardt (LM) algorithm and it has two processes MNN training and MNN testing. LM algorithm is used to train the MNN. These processes are used to provide the CE for different combination of antennas. The performance of the MNN-MIMO-CE method is evaluated in comparison with the existing method [25] through simulations using BER as the performance measure.

Key words: MIMO, Mobile networks; Feedforward neural network, Back propagation, Levenberg-Marquardt algorithm, Channel estimation, Signal to noise ratio and Bit error rate

1. INTRODUCTION

MIMO is widely used configuration system and it has the capacity to offer fast, reliable high throughput wireless link [1]. Frequency selective channel is modified into parallel set of frequency flat sub-channels in OFDM technology [2]. Combination of both the technologies is a major breakthrough for mobile wireless system applications [3-5]

The major problem area in MIMO-OFDM system is channel equalization. The transmitted sequence is affected with both linear and non-linear distortions in the channel. Equalization is done to minimize the effects of those distortions. Though multi path transmit and receive antennas which are used in MIMO increase the capacity it results in increased complexity of channel equalization at the receiver [6-7].High bandwidth efficiency, simple and efficient implementation and reduction of ISI are offered by OFDM [2,8]. Many algorithms were proposed to remove the ISI, to separate different signals and to improve the convergence properties [9-13].

But Neural Network based approaches under machine learning are emerging as efficient algorithms. Nonlinear mapping is better done through Neural Networks than through other methods. Hence signals can be effectively processed through nonlinear channels using neural networks. The natural structure of neural network which has multiple inputs and multiple outputs is more suitable for MIMO systems [10-14]. Conventional feed forward neural networks viz., radial basis function(RBF), back propagation (BP), multilayer perception(MLP) have been employed for MIMO-OFDM system channel equalization[14-17]. Blind equalization using multilayer feed forward perceptron ANN is applied to avoid the Inter Symbol Interference (ISI) which is produced by the bandwidth limited channel with multipath propagation. Three-layer ANN is utilized with the feedback for describing the channel estimation and equalization. The second and third ANN layer comprises of gradient algorithm and kalman filter respectively. These two layers are combined with the feedback of the turbo iteration process to improve the estimation accuracy [18-21]

However, the noise encountered in practical applications is more impulsive in nature than that predicted by Gaussian distribution. Underwater acoustic noise, low frequency atmospheric noise and many types of man made noises are few examples. To model these types of noises α-stable distribution is used [22]. Authors of [23-24] proposed a Fractional Lower-Order Multi-User Constant Modulus Algorithm (FLOS-MU-CMA) to handle robustly α-stable noise and interference in the data. FLOS_MU_CMA is developed for removing the non-Gaussian impulsive noise. The system performance is resolved by the fractional lower order constant. The multiuser constant modulus algorithm cost function was generalized and a new blind equalization algorithm was defined [25] in impulsive noise environment.

Hence in this paper blind channel equalization environment using multilayer neural network named MNN-MIMO-CE is proposed. This technique performs much better and solves equalization problem. The major contribution of this research paper is stated as follows:

- The effective channel estimation is performed by using artificial intelligence such as Multi-layer Neural Network.
- By using this MNN, the noiseless signal transformation is performed over the antennas.

The rest of the paper is organized as follows. Section 2 discusses MNN-MIMO-CE methodology and, Feed forward ANN algorithm with back propagation with LM algorithm is given in section 3. Channel model is discussed in section 4. Simulation results are discussed in section 5 and finally, conclusion is summed up .

2.MIMO SYSTEM MODEL

Consider the MIMO technology has numerous transmitting and receiving antennas at the input and output for making an effective data transmission without crosstalk interference in the wireless communications. The data are simultaneously transferred in a single channel by multiple data streams. The multi path signals are gathered by the multiple data streams through the H.

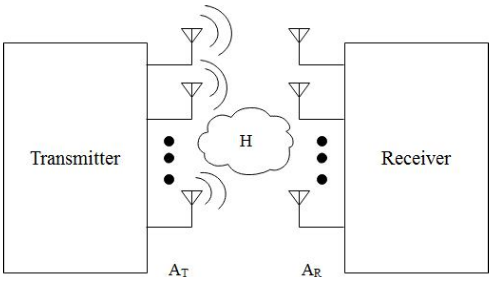


Figure 1: Basic block diagram of MIMO

Where A_T and A_R are the amount of transmitting and receiving antennas respectively.

The coverage and reliability of the system are developed by sending the information at the same speed. The data which are sent by the transmitter is partitioned and it is delivered to the receiver along the transmission of the training sequence named as intermediate samples. This training sequence is used to collect the sufficient amount of information for the channel coefficients to extract the multiple data streams. Each transmit antenna delivers the data in the form of complex symbols that are encoded, modulated, up converted and then it is delivered to the receiver. The signals received by the receiver are base banded, sampled and then it is decoded to discover the information. The basic model for MIMO transmission is shown in Figure 1.

The symbols $x_1[m], x_2[m], \ldots\ldots, x_{A_T}[m]$ are transmitted simultaneously on A_T antennas at m th symbol period and it is expressed in equation (1) as follows,

$$\sum_{k=1}^{A_T} E[|x_k[m]|^2] \le 1 \qquad (1)$$

The signals received by the A_R antennas is given below in equation (2):

$$y_1[m] = \sqrt{P}\,(h_{11}x_1[m] + h_{12}x_2[m] + \ldots + h_{1A_T}x_{A_T}[m]) + w_1[m],$$
$$y_2[m] = \sqrt{P}\,(h_{21}x_1[m] + h_{22}x_2[m] + \ldots + h_{2A_T}x_{A_T}[m]) + w_2[m],$$
$$\cdot \quad \cdot \quad \cdot$$
$$y_A[m] = \sqrt{P}\,(h_{A1}x_1[m] + h_{A2}x_2[m] + \ldots + h_{AA}x_A[m]) + w_A[m], \qquad (2)$$

Where P represents the total transmit power, channel coefficient among the j th transmit antenna to the k th receive antenna is h_{jk} and the AWGN occurred in the k th receive antenna as $w_k(m) \sim CN(0, \sigma_w^2)$.

The transmission matrix in the form of complex coefficients is expressed as follows in equation (3):

$$H = \begin{bmatrix} h_{11}\ h_{12}\ h_{13} \ldots h_{1A_T} \\ h_{21}\ h_{22} h_{23} \ldots h_{2A_T} \\ \ldots\ldots\ldots\ldots\ldots \\ h_{A_R1}\ h_{A_R2}\ h_{A_R3} \ldots h_{A_RA_T} \end{bmatrix} \qquad (3)$$

The channel matrix H is the major factor to know the characteristics of the propagation channel and it is used to generate the correlation among the complex inputs and complex outputs at the receiver.

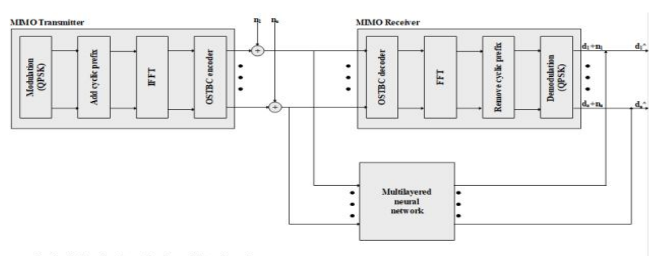
Let $x[m] = [x_1[m], x_2[m], \ldots\ldots, x_{A_T}[m]]_T$ and $y[m] = [y_1[m], y_2[m], \ldots\ldots, y_{A_R}[m]]^T$ be the input and output of the MIMO. The received signal in the vector form is expressed in equation (4) as follows:

$$y[m] = \sqrt{P}Hx[m] + w[m] \qquad (4)$$

Where the channel matrix H is given in equation. (4) and AWGN with zero mean as well as covariance matrix $\sigma_w^2 I_{A_T \times A_R}$ are represented as $w[m] = [w_1[m], w_2[m], \ldots\ldots, w_{A_R}[m]]^T$.

3. MNN-MIMO-CE” METHODOLOGY

The “MNN-MIMO-CE” system mainly comprises of two parts such as MIMO system and MNN. Here MIMO system used for data transmission and MNN provides the CE for noiseless data transmission. The CE is depends on the number of transmit and receive antennas of MIMO system. Finally, it transmits the data with respect to the CE. “MNN-MIMO-CE” method is used to improve the SNR and BER parameters. The Figure 2 shows the block diagram of the MNN-MIMO-CE method.



A. Multi layer Neural Network(MNN)

MNN is used for estimating the channel while performing data transmission over the MIMO. The MNN primarily carries the nonlinear functional blocks named as neurons, which are linked with the parallel synaptic weights. This ANN is used for avoiding the nonlinear relationships inside the network. The inputs from the MIMO have some weight which is related to the synaptic efficacy in the biological neuron. The synaptic weights are modified by the neural network. The single threshold value is maintained in each neuron.

1) MNN training

MNN doesn't have any closed paths and the output nodes are linked with the input nodes without any feedback paths. Here, two kinds of inputs are given for training purpose such as channel estimation and received signal as a target value. Since, the CE is depends on the seven different factors such as sampling rate, path delay, average gain, maximum doppler shift, spatial correlation, number of transmitter and receiver antennas. The global minimum is obtained by using the Levenberg-Marquardt (LM) algorithm in Back Propagation Algorithm (BPA) and this LM algorithm is used for training the MNN. This neural network has one or more hidden layers of sigmoid neurons followed by an output layer of linear neurons as well as it is used as a general function approximator. The hidden layer has an adequate amount of neurons to approximate any function with a finite amount of discontinuities. The structure of MNN is illustrated in Figure.3.

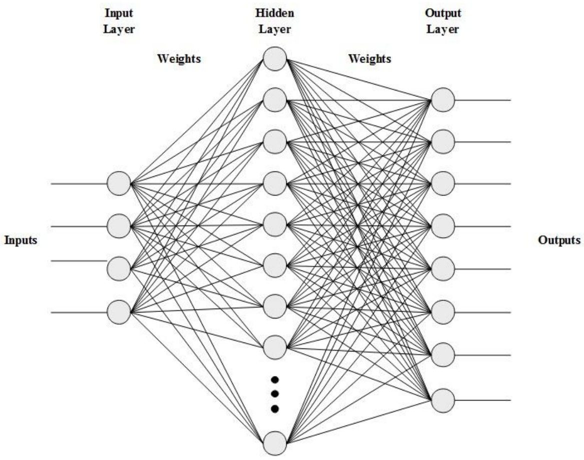


Figure.3:. Multilayered Neural Network Structure

a. Levenberg–Marquardt algorithm

The training of MNN is depends on the Levenberg–Marquardt (LM) algorithm, it is generally a hessian based algorithm which is used for nonlinear least square optimization. In LM training of MNN, the objective function that is $E(w)$ is minimized for adjusting the synaptic weights of input to hidden layer and hidden layer to output function and then the following equation (5) shows the objective function.

$$E(w) - \frac{1}{2}\sum_{k=1}^{c}(d_k - o_k)^2 \qquad (5)$$

Where, the kth transmitter desired output and actual output is represented as d_k and o_k respectively and c describes the amount of output points. The weights of the MNN is updated for reducing the objective function. The weight updation is given in the equation (6).

$$\Delta w = -[J^T J + \mu I]^{-1} J^T E \qquad (6)$$

Where, the J represents the jacobian matrix and this matrix comprises of first derivatives of the network errors with related to the weights and biases. μ describes the learning rate and this is used for describing the how much amount of weight which is changed in each step. The MNN is trained faster when the network has high learning rate and also it accelerates the training process. The higher amount of learning rate induce the network oscillations which slow down the convergence. MNN with smaller amount of learning rate takes more time to converge. The minimum and maximum amount of learning rate is 0.0 and 1.0 respectively.

So, in this MNN-MIMO-CE takes the μ has 0.05.

The MNN-MIMO-CE training steps are given as follows:

1. The weight and learning rate are initialized.
2. The objective function (i.e., sum of squared error) among the desired and actual outputs are calculated.
3. The weight update formulae which is given in following equation (7) is solved.

$$X_j(2k) = \frac{H_{j1}^*(k)Y_j(2k) + H_{j2}^*(k)Y_{j2}(2k+1)}{\left|H_{j1}^*(k)\right|^2 + \left|H_{j2}^*(k)\right|^2} \qquad (7)$$

Where, the $X_j(2k)$ is the transmitted data and transmitted data of frequency domain is $H_{ij}(k)$.

4. By using the $w + \Delta w$, the squared error is again calculated. The learning rate is reduced 0.1 times, when the error is smaller than the computed one else then increase the learning rate 10 times and go to the step 3.
5. This training of MNN-MIMO-CE is stopped until the error is less than the predetermined value.

2) MNN Testing

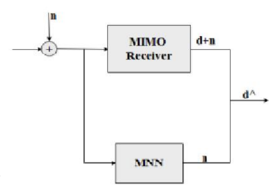


Figure.4: MNN Testing block diagram

The block diagram of the MNN testing is shown in Figure 4. Where n and d is the noise and signal which is sent via the MIMO system respectively. In this process, channel data is given to the MIMO receiver. This testing data is evaluated with the trained data of the MNN. Based on the trained data, the MNN testing gives the optimal signal to the receiver. It leads to decrease the noise level when compared to the MIMO system without CE. The detailed explanation about MNN testing is given as follows:

The MIMO-OFDM symbols contains the complex signals. But, the neural network accepts only the real signals. For that each complex signal is divided into real and imaginary values. After performing MNN training, the real parts of the signals that is channel data is given to the MNN testing and this testing criteria provides the received signal with respect to channel data. Here, the activation function is used for computing the nodes inputs such as the input signals which are divided into real and imaginary values and weight sums. The mathematical expression for the activation function is expressed in equation (8).

$$net_j = \sum_{i=0}^{L_1} S_i w_{ij} \quad (8)$$

$$o_j = f(net_j) = \frac{e^{2net_j}-1}{e^{2net_j}+1} \quad (9)$$

Where weight of input to hidden layer at j th node is w_{ij} and L_1 is the number of input neurons. The activation function which is computed in the output layer for an each nodes is given in equation (10).

$$net_k = \sum_{j=1}^{L_2} o_j w_{jk} \quad (10)$$

$$o_k = f(net_k) \quad (11)$$

Where weight of input to hidden layer at k th node is w_{jk} and L_2 is the number of hidden layer nodes. The following equation (12) shows anyone of the neural estimator output.

$$o_k = f(net_k) = f\left(\sum_{j=1}^{L_2} w_{jk} f\left(\sum_{i=0}^{L_1} w_{ij} f(w_{ij} S_i)\right)\right) \quad (12)$$

The noise values of an entire signal is estimated by adding each parts of the inputs.

b. CHANNEL MODEL

The channel model of MNN-MIMO-CE system is AWGN. Impulsive noise is sporadic, non-contiguous, consisting of irregular pulses or noise spikes of short duration and of relatively high amplitude as well as high/several hundreds of micro-volts are occurred at bursts or discrete impulses and Figure 5 shows the block diagram of the channel model and impulsive noise environment.

In order to describe the impulsive noise characteristics, a mathematical model is needed. For that Bernoulli-Gaussian impulse noise model is described. The characteristics function of the Bernoulli distribution is given in equation (13) as follows,

$$C_F = q + e^{it} \quad (13)$$

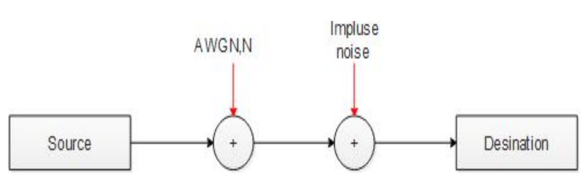


Figure. 5: Gaussian and impulse noise channel

The signal s transmitted over a channel with impulsive noise I_n and White Gaussian noise N and the signal R received are described by the following equation (14).

$$R = S + N + I_n \quad (14)$$

N is AWGN with mean zero and variance 2σ and I_n is the impulsive noise. I_n is a product of AWGN and Bernoulli process, also: $I_n = b.n$. All these parameters are assumed to be complex and independent of each other. Then the characteristic function $\phi(\omega_1+\omega_2)$ of total noise of $N_t = N + I_n$ is given as follows

$$\phi_{nk}(\omega_1+\omega_2) = e^{\frac{-\sigma^2\omega(\omega_1^2+\omega_2^2)}{2}}\left[(1-P)+Pe^{\frac{-\sigma^2\omega(\omega_1^2+\omega_2^2)}{2}}\right] \quad (15)$$

The realistic characteristics of real impulsive noise function are given in equation (15).

4. RESULT AND DISCUSSION

MNN-MIMO-CE system was implemented by using MATLAB 2017b software tool with communication and Neural Network toolbox (for the simulation purpose). The MNN-MIMO-CE system consists of two sections such as, training and testing. Training is the major important part of the system, MNN training is carried out by using the parameters in table I and the training diagram of MNN is given in Figure.6.

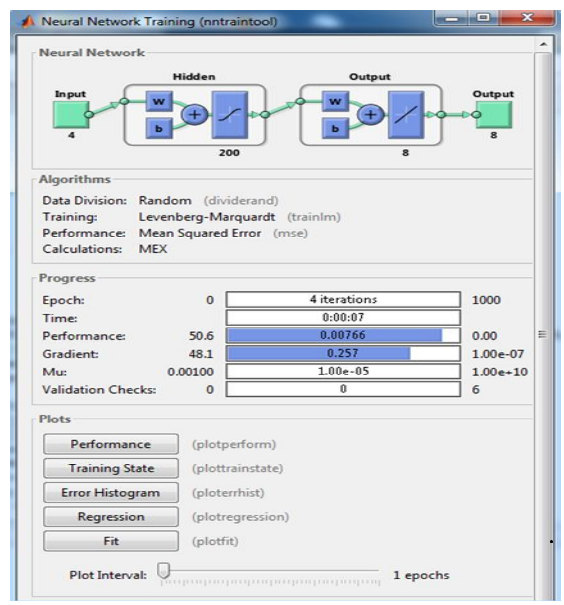


Figure. 6: Neural network training

The testing of the MNN-MIMO-CE system is done by the testing parameters in table II. The second part of the MNN-MIMO-CE system is tested, in that 100 random bits' data are generated (with the sampling rate 1e6 and block size is 32).

Table 1: PARAMETERS FOR MNN TRAINING

ANN-MIMO-DF system Neural Network training	
Data bits	300 random bits data's (with pocket size of 32)
Sampling rate	1e6
Path delays	0 to 2e-6
Neural Network inputs	4
Neural Network outputs	8
Hidden layers	200

The generated data are sent to the modulation section. The QPSK modulation technique is used, so the output of the modulator is in the form of 50X1 complex double format. The next step is combining the input with cyclic prefix data which is generated by using this floor (0.5 * length (mod Data)) command. The generated data is in the Form of 75X1 double. Cyclic prefix insertion is used to protect the OFDM signal from inter symbol interference (ISI) and it is done with the help of cyclic prefix and modulated data

Table 2: PARAMETERS FOR MNN TESTING

ANN-MIMO-DF system Testing	
Data bits	100 bits data's (with pocket size of 32)
Sampling rate	1e6
Path delays	0 to 2e-6
Modulation & demodulation	QPSK
Channel encoding & decoding	STBC
Channel type	AWGN + Impulse noise channel
Antenna type	2X1, 2X2, 4X2, and 4X4
SNR value for analysis	0:2:25

The output of the IFFT is in the Form of 75X1 complex double format. Output data is passed through the STBC encoder, the transmitted signals are propagated through the AWGN and impulsive noise channel environment, in that the white Gaussian noise and impulsive noise are added depending upon the SNR value (0 to 25). The noise affected transmitted signal is received by the receiving section (2X2 and 4X4) antennas, at the time the channel estimation is done with the help of Neural network and the output data is given to STBC decoder. The decoder decodes the signal, then the FFT process and the cyclic prefix removing process and QPSK demodulation are applied to the received signal and the output data is received. Finally, the performance is calculated and compared with the existing system [25].

Figure 7 shows the comparison of 2x2 MNN-MIMO-CE system with the existing system [25] in AWGN channel. In that SNR Vs Bit error rate is compared and it shows that the MNN-MIMO-CE system obtained a low bit error rate.

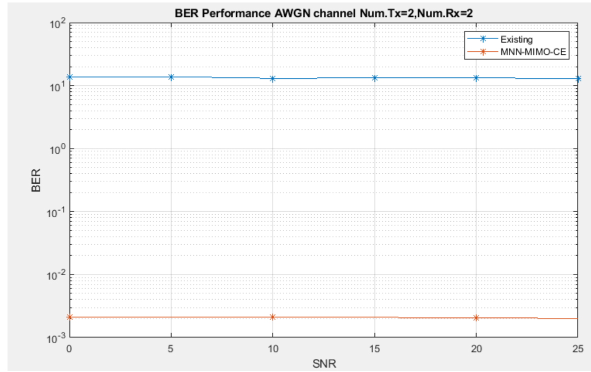
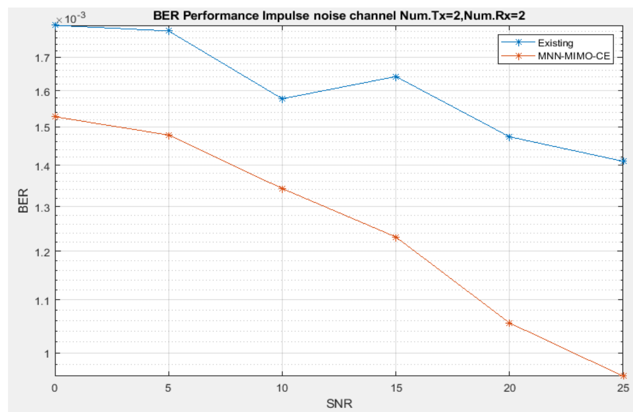


Figure.7.MNN-MIMO-CE system comparison with the existing system [25] in AWGN channel

Figure 8 shows the comparison of 2x2 MNN-MIMO-CE system and the existing system [25] in an impulsive noise channel. In that S NR Vs Bit error rate is compared and it shows the MNN-MIMO-CE system achieves a low bit error



rate.

Figure8:2x2MNN-MIMO-CE system comparison with the existing system [25] in impulse noise channel

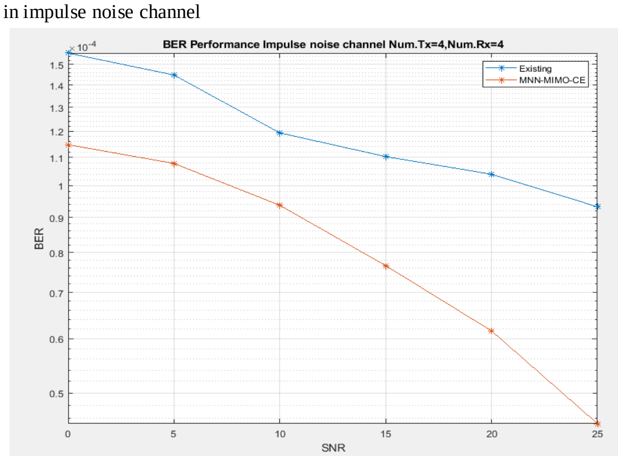


Figure 4 .4x4 ANN-MIMO-DF system comparison with the existing system [25] in impulse noise channel.

Figure 9 shows the comparison of 4x4 MNN-MIMO-CE system and the existing system [25] in an impulse noise channel. In that SNR Vs Bit error rate is compared and it shows the MNN-MIMO-CE system has low bit error rate when compared to existing system.

The graphical representation of Figure 7, Figure 8 and Figure 9 shows that the BER of MNN-MIMO-CE is smaller than the existing system [25]. Because the existing system [25] (i.e., fractional lower-order multi-user constant modulus algorithm) was performed channel estimation based on the cost and weight functions. This method doesn't consider any training sequences while performing channel estimation. But, in this MNN-MIMO-CE method the training sequences are considered in channel estimation. Based on that, the better channel estimation is performed to reduce the BER performances and it improves the SNR of the signal which is transmitted through the MIMO.

5. CONCLUSION

A multilayered NN for Blind Adaptive equalization of MIMO system in impulsive noise environment is proposed. In the MNN-MIMO-CE technique LM algorithm is used to train the network with 200 hidden layers having 4 input nodes and 8 output nodes. MNN-MIMO-CE technique is established by introducing the OFDM signal transmission between the MIMO transmitter and receiver as well as MNN is introduced for providing the channel estimation to minimize the error rates in MIMO system. Simulation results have illustrated the effective equalization properties of the proposed MNN-MIMO-CE method in impulsive noise environments. The obtained results show that the MNN-MIMO-CE method has lesser BER compared to the existing method by Li Sen et all [25].

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